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RoboLeader: Dynamic Re-Tasking for Persistence Surveillance in an Urban Environment Using Robot-to-Robot Control

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14. ABSTRACT
In the FY09 DRI, we developed the RoboLeader intelligent agent that had the capabilities of coordinating a team of ground robots and revising route plans for the robots based on battlefield intelligence. In the current DRI, the capabilities of RoboLeader were expanded to deal more specifically with dynamic re-tasking requirements based on battlefield developments as well as coordination between aerial and ground robots in pursuit of moving targets. The results of our human-in-the-loop simulation experiment showed that RoboLeader (Fully Automated condition) was more effective in encapsulating the moving targets than were the human operators (when they were either without assistance from RoboLeader [Manual] or when they were partially assisted by RoboLeader [Semi-Autonomous]). Participants successfully encapsulated the moving targets only 63% of the time in the Manual condition but 89% of the time when they were assisted by RoboLeader. Those participants who play video games frequently demonstrated significantly better encapsulation performance than did infrequent gamers; they also had better SA of mission environment. Visualization had little effect on participants' performance. Finally, participants reported significantly higher workload when they were in the Manual condition than when they were assisted by RoboLeader.

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1. Objective

Unmanned vehicles (UVs) are being used more frequently in military operations, and the types of tasks they are being used for are evolving in complexity. In the future battlefield, Soldiers may be given multiple tasks to perform concurrently, such as navigating a UV while conducting surveillance, maintaining local security and situational awareness (SA), and communicating with fellow team members. In order to maximize human resources, it is desirable to designate a single operator to supervise multiple UVs simultaneously. However, past research has shown that human operators are often unable to control multiple robots/agents simultaneously in an effective and efficient manner (*1, 2*). Additionally, as the size of the robot team increases, the human operators may fail to maintain adequate SA when their attention has to switch constantly among the robots, and their cognitive resources may be overwhelmed by the intervention requests from the robots (*3, 4*). Wang et al. reviewed a number of studies on supervisory control of multiple ground robots for target detection tasks and concluded that "the Fan-out plateau lies somewhere between 4 and 9+ robots depending on the level of robot autonomy and environmental demands" (*4*, p. 143).

Research shows that autonomous cooperation between robots can aid the performance of the human operators (*3*) and enhance the overall human-robot team performance (*2*). However, in the foreseeable future, human operators' involvement in mixed-initiative teams will always be required, especially for critical decision making. Human operators' decision making may be influenced by "implicit goals" of which the robots are not aware (i.e., items that are not programmed into the behaviors of the robots) (*5*). In addition, real-time development on the battlefield may require the human operator to change the plan for the robot team and/or for individual robots. Therefore, effective communication between the human operator and the robots is critical in ensuring mission successes (*6*). To achieve a better balance of enhancing autonomy and capability while simplifying human-robot interaction, we developed an intelligent agent called RoboLeader, a robotic surrogate that could help the human operator coordinate a team of ground robots (our FY09 Director's Research Initiative [DRI]) (*7*). In other words, instead of directly managing the robot team, the human operator only dealt with RoboLeader; consequently, the operator could better focus on the other tasks requiring attention. In Chen et al. (*7*), the effectiveness of RoboLeader was investigated in a human-in-the-loop simulation experiment. Chen et al. compared the operators' target detection performance in a four- and eight-robot condition. The results showed that participants detected significantly fewer targets with eight robots versus four robots. Although there were no significant differences between the RoboLeader and baseline (no RoboLeader) conditions for target detection, the RoboLeader group reduced their mission completion times by approximately 13% compared to the baseline group. Those participants with higher spatial ability detected more targets than did those with lower spatial ability. Participants experienced significantly higher workload with eight robots

compared to the four-robot condition, and those with better attentional control reported lower workload than did those with poorer attentional control.

In the current study, the capabilities of RoboLeader were expanded to deal more specifically with dynamic re-tasking requirements for persistent surveillance of a simulated urban environment based on various battlefield developments as well as coordination between unmanned aerial vehicles (UAVs) and unmanned ground vehicles (UGVs) in pursuit of moving targets in urban environments. More specifically, the participants used four UGVs to "chase" a moving target via a map that displays the location of the target via a UAV link while monitoring the streaming videos from the four UGVs. The levels of autonomy of RoboLeader were manipulated (see section 2.3). Additionally, we investigated the effects of individual differences in spatial ability (SpA) and perceived attentional control (PAC) on the operators' robotics control as well as multitasking performance.

Previous research has found performance differences on certain tasks between individuals with high and low SpA. Lathan and Tracey (*8*) demonstrated that people with higher SpA finished their tasks faster and had fewer errors during a teleoperation task through a maze. Lathan and Tracey suggested that military missions can benefit from selecting personnel with higher SpA to operate robotic devices. Our previous studies also found SpA to be a good predictor of the operator's robotics performance (*1, 7*). In Chen et al. (*7*), participants with higher SpA scanned the videos significantly faster than those with lower SpA. In the current experiment, we also examined the relationship between attentional control and multitasking performance. Several studies show that there are individual differences in multitasking performance, and some people are less prone to performance degradation during multitasking conditions (*9*). There is also evidence that people with better attentional control can allocate their attention more flexibly and effectively (*10*), which was partially confirmed by Chen and Joyner (*11*).

In the current study, we manipulated the level of autonomy of RoboLeader and examined its effect on the operator's performance (i.e., plan revisions for the robots, the concurrent target detection task, and SA of the mission environment) and workload. The four levels of manipulation were as follows: Manual, Semi-Autonomous without Visualization, Semi-Autonomous with Visualization, and Fully Automated. The Semi-Autonomous condition was divided into two conditions so that the effect of the visualization tool could be evaluated. The visualization tool informed the participant of the synchronization of the robots as well as overall entrapment effectiveness of the target based on the movement of the target (see section 2.2.2). The effects of operator individual differences in spatial ability and attentional control were also investigated.

There were two major risks that needed to be overcome in order for this DRI to be successful. One was developing the algorithms for the RoboLeader system and its interaction with the human operator as well as individual robots under its control. In human-robot interaction research, predetermined (canned) simulations are often used to simulate automated capabilities.

In this DRI, RoboLeader was capable to provide real-time solutions to the human operator based on the operator's responses. Another risk involved in this DRI was developing the visualization tool. While visualization techniques have been researched for a long time, not much research has been conducted in the area of providing real-time visual feedback to operators about their planning task.

2. Approach

2.1 Participants

Twenty-eight individuals in the Orlando, FL, area (3 females and 25 males, mean age 21 years) participated in this study. They were compensated $15 per hour for their participation.

2.2 Apparatus

2.2.1 Simulator

The Mixed Initiative Experimental (MIX) Testbed used in the first RoboLeader experiment was modified and used as the simulator for this experiment (*7*). The MIX Testbed is a distributed simulation environment for investigating how unmanned systems are used and how automation affects human operator performance. The Operator Control Unit (OCU) of the MIX Testbed was modeled after the Tactical Control Unit developed under the U.S. Army Research Laboratory (ARL) Robotics Collaborative Technology Alliance. This platform includes a camera payload and supports multiple levels of automation. Users can send mission plans or teleoperate the platform with a computer mouse while being provided a video feed from the camera payload. Typical tasks include reconnaissance and surveillance. RoboLeader is capable of collecting information from subordinate robots with limited autonomy (e.g., with capability of collision avoidance and self-guidance to reach target locations), making tactical decisions, and coordinating the robots by issuing commands, waypoints, or motion trajectories (*7*).

2.2.2 RoboLeader

The RoboLeader user interface is shown in figure 1. The map was located in the upper-left corner and showed the location of the moving target (a slowly moving truck) via a link to a UAV flying over the mission area (i.e., the icon representing the truck was displayed as an arrow to show the direction of movement and continuously moved on the map display based on the truck's actual movement, which was updated from the UAV). The right half of the screen was divided into four separate camera feeds, streaming from the four UGVs. The visualization display was located in the lower left corner of the OCU. The four vertical bars had the words, "NEAR" and "FAR" at the top and bottom of each bar, respectively, and represented the scores for each robot's synchronization with the moving target; the horizontal bar represented the aggregate entrapment score of the robots' plans. As the target moved, RoboLeader calculated the

scores based on each robot's plan as well as the speed and movement of the target and showed the scores via the bar graphs. The vertical bars filled with the color green as a specific UGV got closer to the target or filled with red as a UGV got farther from the target. Additionally, a red arrow was displayed to the right of each graph if a UGV was moving away from the target (see figure 1). RoboLeader continuously updated the calculations and visualizations (bar graphs) until the target was captured (cornered by at least two UGVs), at which time the scenario ended.

Figure 1. RoboLeader operator control unit.

The primary driver algorithm implemented for RoboLeader was based on the A-Starr algorithm and is a one-step search routine (*12*). In its basic form, the design was used to efficiently track between two way points: a starting point and an ending point, where the starting point was typically the current position of an intercept vehicle and the ending point was a designated target intercept point. Once a target location and heading was identified within the terrain, RoboLeader determined all possible approach routes to the target and then determined which vehicle should track to a particular intercept location.

Figure 2 depicts the layout of a target within an urban street terrain. In this particular case, four street intersections comprise possible approach routes for the intercept vehicles whereas three intersections are of primary concern in order to block possible escape routes. In order to fully encapsulate a target, however, intercept vehicles must be dispatched to the primary intercept routes first and then any remaining vehicle assets can then be assigned to fall in behind the target in a tail-chase fashion. Once all target intercept points are identified, every possible path between each vehicle and target intercept points is calculated and logged into temporary memory. In other

words, for each vehicle, a path is calculated from that vehicle to *each* of the target intercept points, which results in $n \cdot t$ calculated paths, where n is the number of intercept vehicles and t is the number of target intercept routes. RoboLeader calculates the length of each of these paths and stores this data into temporary memory as well.

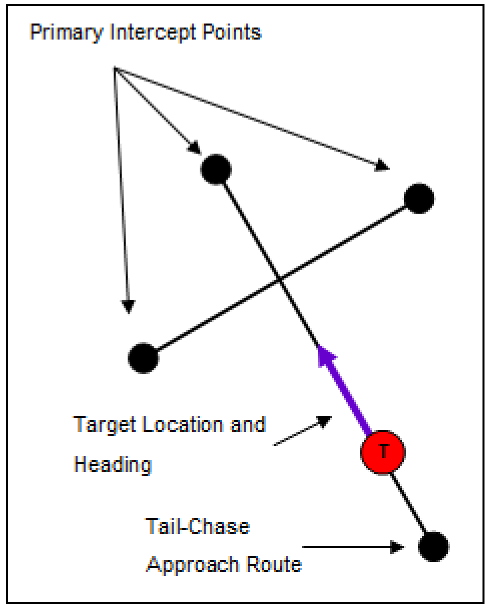

Figure 2. Target intercept geometry.

In order to determine which vehicle gets assigned to particular target approach point, RoboLeader analyzes the collected path data and specially arranges that data with the help of C++ sort predicates. RoboLeader then identifies the vehicle with the closest approach route to the target and commands that vehicle to navigate to the appropriate intercept point. This process continues, giving the next closest vehicle precedence until all assets are allocated. Once nested within the real-time environment of the Mix Testbed, the target tracking and vehicle allocation process occurred iteratively at a set rate. Therefore, each time the RoboLeader algorithm was called, fresh new target data were gathered and target intercept trajectories calculated. This ensured constantly updated target entrapment routes in real time.

In addition to real-time target entrapment, RoboLeader also provided real-time assessment of participants' target entrapment performance, which was displayed in the visualization components of the RoboLeader user interface. In the two conditions when the visualization tool was unavailable (Manual and Semi-Autonomous without Visualization), RoboLeader calculated the encapsulations scores (for data analysis purposes) but did not provide feedback to the operators. There were two levels of feedback on target tracking and entrapment:

- *Directional Metric*. The first metric was a directional indicator and was expressed with respect to relative headings between the intercept vehicle and the target. Because vehicle motions were constrained within an urban setting, it was important to know whether the

overall motion of the intercept vehicle was trending toward, parallel to, or away from the target. Establishment of a line of sight (LOS) between each of the intercept vehicles and the target was important in determining the relative directional trend. To do this, a simple vector projection equation was used that projected the intercept vehicles heading vector onto the LOS. The separation angle between the LOS and heading vector was then calculated. Figure 3 shows how the metric was formed. V represents the intercept vehicles heading with respect to the LOS.

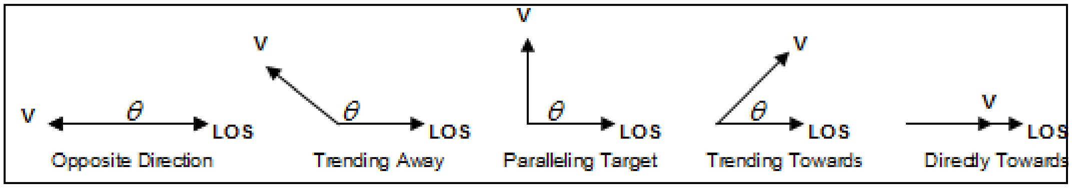

Figure 3. Directional metric calculation.

The angle θ range is $(\pi,0)$ whereas the cosine of the angles range is $-1 \le \cos\theta \le +1$ and therefore, the calibration of the directional indicator is scaled directly to the cosine of the angle where –100% indicates that the intercept vehicle is moving in the opposite direction to the target and +100% indicates that the intercept vehicle is moving directly at the target.

- *Entrapment Metric*. The second metric measured how well the target escape routes had been blocked by intercept routes. As discussed previously, a target could only have a set number of escape paths from its current position. The RoboLeader algorithm determined these escape routes and assigned intercept vehicles to these points in order to make an intercept. The entrapment score was simply based on how many of these escape routes had an intercept vehicle assigned to them.

2.2.3 Surveys and Tests

A demographics questionnaire was administered at the beginning of the training session. An Ishihara Color Vision Test (with nine test plates) was administered via PowerPoint® presentation. Since the RoboLeader OCU employed several colors to display the plans for the robots, normal color vision was required to effectively interact with the system. A questionnaire on Attentional Control (*10*) was used to evaluate participants' perceived attentional control. The Attentional Control survey consists of 20 items and measures attention focus and shifting. The scale has been shown to have good internal reliability ($\alpha = 0.88$). The Cube Comparison Test (*13*) and the Spatial Orientation Test (*14*) were used to assess participants' spatial ability. According to Neumann (*15*), these two tests measure different aspects of spatial ability. The Cube Comparison Test requires participants to compare, in 3-min, 21 pairs of six-sided cubes and determine if the rotated cubes are the same or different. The Spatial Orientation Test, modeled after the cardinal direction test developed by Gugerty and his colleagues (*14*), is a

computerized test consisting of a brief training segment and 32 test questions. Both accuracy and response time were automatically captured by the program.

Participants' perceived workload was evaluated with the computerized version of the National Aeronautics and Space Administration Task Load Index (NASA-TLX) questionnaire, which used a pairwise comparison weighting procedure (*16*). The NASA-TLX is a self-reported questionnaire of perceived demands in six areas: mental, physical, temporal, effort (mental and physical), frustration, and performance. Participants evaluate their perceived workload level in these areas on 10-point scales as well as complete pairwise comparisons for each subscale. A modified version of the Usability survey used in Chen and Terrence (*17*) was used to assess participants' perceived usability of the RoboLeader system as well their trust in the system. The items that assessed participants' trust in the system were modified from the "Trust Between People and Automation" survey (*18*).

2.3 Procedure

After being briefed on the purpose of the study and signing the informed consent form, participants completed the demographics questionnaire and the Attentional Control survey, and were administered a brief Ishihara Color Vision Test to ensure they had normal color vision. After the Color Vision Test, the participants completed the two spatial ability tests. Participants then received training and practiced on the tasks they would need to conduct during the experimental session. Training was self-paced and was delivered by PowerPoint slides showing the elements of the OCU, steps for completing various tasks, several mini-exercises for practicing the steps, and exercises for performing the robotic control tasks. The training session lasted approximately 1 h.

The experimental session lasted about 1.5 h and began immediately after the training session. Each experimental session had four scenarios (corresponding to the four experimental conditions; however, the pairing of scenarios and conditions was counterbalanced), each lasting approximately 20 min. During the scenarios, participants used their four robotic assets to pursue a primary moving target (a truck traveling at about 3 MPH) while monitoring the streaming videos from the robots in order to find additional (secondary) targets (insurgents carrying weapons) in the mission environment. When the scenario for the Manual condition started, the participants put in waypoints for each UGV manually and adjusted the waypoints based on the movement of the primary target. In the Semi-Autonomous conditions, the participant selected an end point/location for the UGV at which time RoboLeader provided an optimum solution with how to reach the desired destination. With the visualization condition, the user might consult the bar graphs as an indicator of whether their point selections were effective in terms of synchronization of the robots and entrapment of the target or if the plans needed revisions. The scores displayed in the visualization area were calculated based on the RoboLeader's encapsulation algorithm. Without visualization, the participant had to determine if they were properly cornering the target for capture. In the Fully Automated condition, RoboLeader

provided the recommended end points as well as intermediate waypoints for each robot. The participant could accept, modify, or reject the plans. In each scenario, there were hostile areas (indicated by red squares on the map) that the robots needed to avoid. The order of experimental conditions was counterbalanced across participants.

The robots did not have aided target recognition capability; therefore, the participants had to detect the insurgents (secondary targets) by themselves. For the insurgent targets, participants used a mouse to click the Insurgent button on the interface and then click on the insurgent to “laze” them as soon as they were detected. The “lazed” insurgent was then displayed on the map. Additionally, there were civilians as well as friendly Soldiers in the simulated environment to increase the visual noise present in the target detection tasks.

Each scenario also contained five SA queries, which were triggered based on time progression (e.g., 3 min into the scenario). The SA queries included questions such as “Use the provided paper to identify which route or routes have encountered the most Insurgents,” etc. When an SA query was triggered, the OCU screen went blank, the simulation was paused, and the SA query was displayed on the screen. Participants then wrote their response to the query on an answer sheet. After participants responded to the SA query, it was removed from the OCU screen and the simulation resumed.

There was a 2-min break between the experimental scenarios. Participants assessed their perceived workload using the NASA-TLX as well as their perceived usability of the RoboLeader user interface using the Usability/Trust survey immediately after each experimental scenario. The entire data collection session lasted about 3 h.

2.4 Experimental Design and Performance Measures

The study was a within-subject design with RoboLeader’s level of autonomy as the independent variable (with four levels: Manual, Semi-Autonomous without Visualization, Semi-Autonomous with Visualization, and Fully Automated). Dependent measures included the participants’ performance of encapsulating the primary target (the encapsulation scores), the percentage of secondary targets (insurgents) detected, the participants’ SA of the mission environment (percentage of SA queries answered correctly), and the participants’ perceived workload. A repeated-measure analysis of variance with RoboLeader as the within-subject factor was used to evaluate the operator performance differences among the four conditions.

3. Results

3.1 Primary Target Encapsulation Performance

The analysis revealed that the level of autonomy of RoboLeader significantly affected the participants' performance of primary target encapsulation, $F(3,24) = 10.61$, $p < 0.0001$ (figure 4). Post hoc comparisons (least significant difference [LSD]) showed that the participants' encapsulation scores in the Fully Automated condition were significantly better than their results in the other conditions. On average, 63% of the participants successfully encapsulated the primary target in the Manual condition; 96% of them did so in the Semi-Autonomous without Visualization condition; 86% in the Semi-Autonomous with Visualization condition and the Fully Automated condition (figure 5). A χ^2 test showed that the percentage of perfect encapsulation in the Manual condition was significantly lower than the average of the other three conditions (i.e., RoboLeader-assisted conditions), $\chi^2 (1, N = 27) = 11.901$, $p < 0.001$. In the Manual condition, participants who play video games frequently (i.e., daily or weekly) performed significantly better than infrequent gamers $\chi^2 (1, N = 7) = 3.857$, $p < 0.05$. On average, frequent gamers successfully encapsulated the target 70% of the times and infrequent gamers did so only 43% of the times. Participants' spatial ability and perceived attentional control did not have effects on their encapsulation performance.

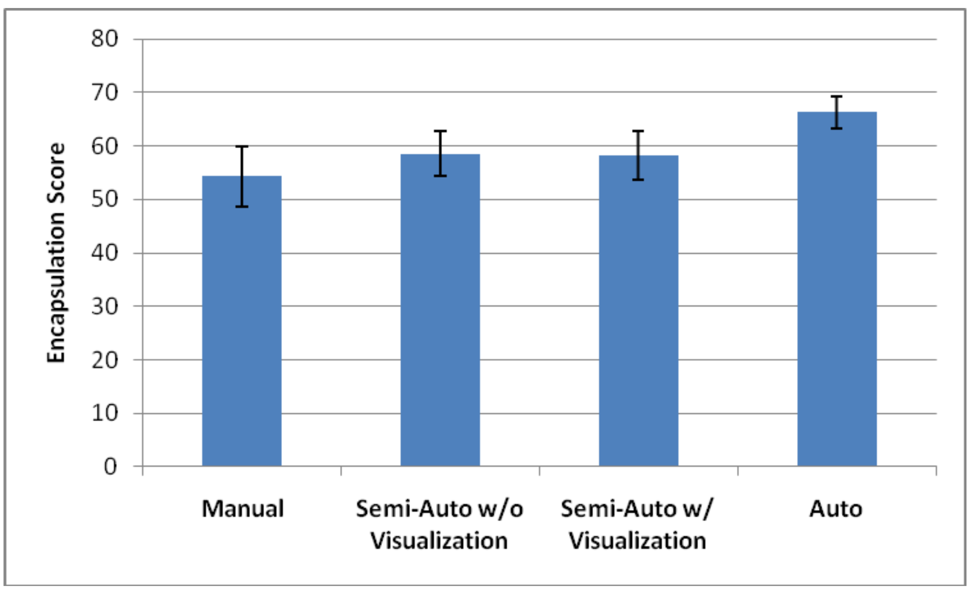

Figure 4. Encapsulation performance.

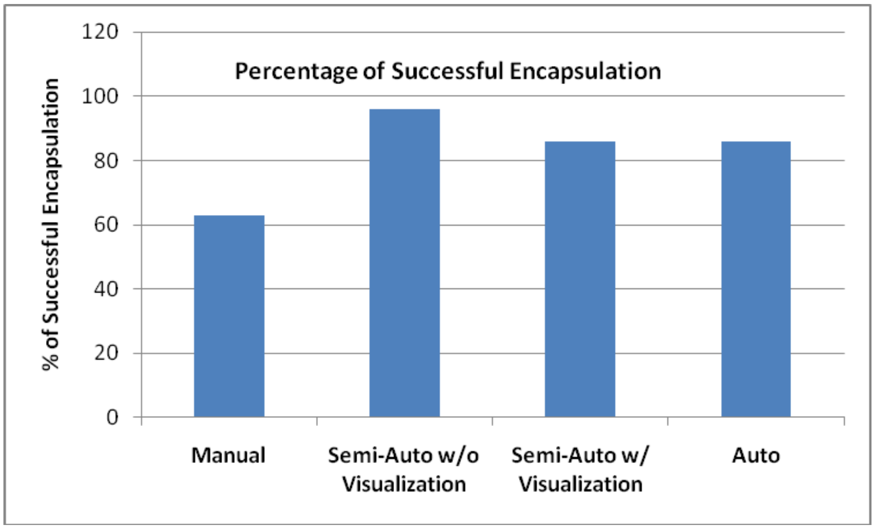

Figure 5. Percentage of participants with successful encapsulation performance.

3.2 Secondary Target Detection Performance

On average, the participants detected approximately two thirds (61–64%) of the insurgents in the mission environment. However, there was not a significant main effect of RoboLeader's level of autonomy on participants' target detection performance. Neither of the individual difference factors (participants' spatial ability and perceived attentional control) had a significant effect on the target detection performance.

3.3 Situational Awareness

The participants' SA of the mission environment did not differ among the conditions. Participants' gaming experience was found to have an effect on their SA, $F(2,24) = 3.476$, $p < 0.05$ (figure 6). Post hoc comparisons (LSD) showed that the daily gamers and weekly gamers outperformed infrequent gamers, $p < 0.05$. There was no difference between daily and weekly gamers.

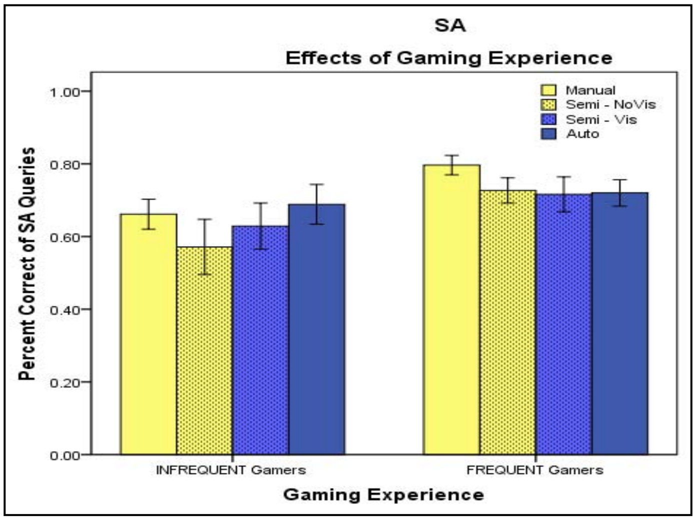

Figure 6. Effects of gaming experience on SA of the mission environment.

3.4 Workload

There was not a significant main effect of RoboLeader's level of autonomy on participants' perceived workload (weighted NASA TLX composite scores; figure 7). However, when the workload assessment in the Manual condition was compared against the aggregated workload assessments of the other three conditions combined, there was a significant difference between the Manual and the RoboLeader-assisted conditions, $F(1,25) = 8.312$, $p < 0.05$. Participants reported significantly higher workload ratings in the Manual condition ($M = 63.87$) than they did in the other three conditions ($M = 58.36$).

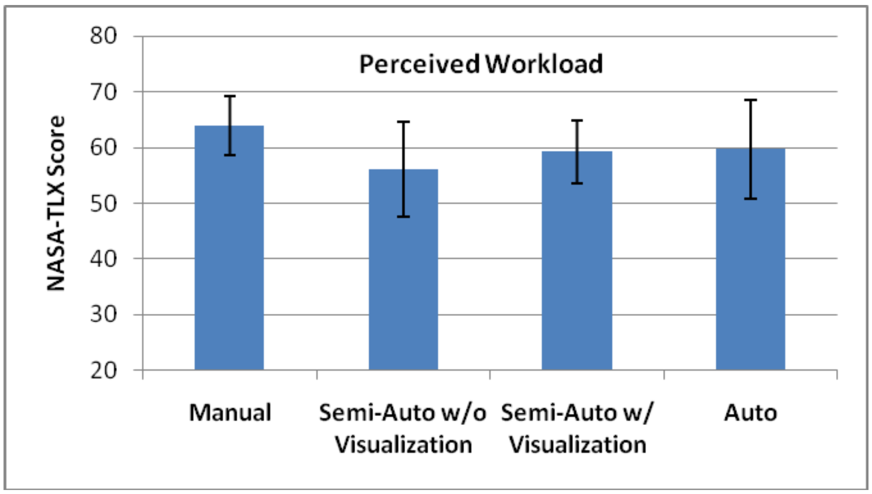

Figure 7. Perceived workload.

4. Conclusions

In the FY09 DRI, we developed the RoboLeader intelligent agent that had the capabilities of coordinating a team of ground robots and revising route plans for the robots based on battlefield intelligence (*7*). In the current DRI, the capabilities of RoboLeader were expanded to deal more specifically with dynamic re-tasking requirements based on battlefield developments as well as coordination between UAVs and UGVs in pursuit of moving targets. The results of our human-in-the-loop simulation experiment showed that RoboLeader (Fully Automated condition) was more effective in encapsulating the moving targets than were the human operators (when they were either without assistance from RoboLeader [Manual] or when they were partially assisted by RoboLeader [Semi-Autonomous]). Participants successfully encapsulated the moving targets only 63% of the time in the Manual condition but 89% of the time when they were assisted by RoboLeader (i.e., the other three conditions combined). Those participants who play video games frequently (daily or weekly) demonstrated significantly better encapsulation performance than did infrequent gamers; they also had better SA of mission environment. These results are

consistent with the findings of one recent U.S. Air Force study (*20*) that frequent video gamers outperformed infrequent gamers on robotics (unmanned aerial systems [UAS]) tasks and, in some cases, performed as well as experienced pilots. It is somewhat surprising that visualization had little effect on the Semi-Autonomous conditions. This suggests that map cues were sufficient for the encapsulation task in the current experiment. It is worth noting that in the current study, the speed of the moving target was fairly slow (about 3 MPH), which made the target encapsulation task relatively easy. If the moving target had traveled at a higher speed, the target encapsulation task would have been more difficult and the utility of RoboLeader and the effects of operator spatial ability might have been even more pronounced. While there was no significant difference in target detection performance among the conditions, the participants reported significantly higher workload when they were in the Manual condition than when they were assisted by RoboLeader. In conclusion, RoboLeader demonstrated significant utility for enhancing human operators' performance as well as reducing their workload.

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6. Transitions

RoboLeader is being evaluated as an intelligent agent for the Safe Operations for Unmanned Vehicles for Reconnaissance in Complex Environments (SOURCE) Army Technology Objective (ATO) to aid operators in finding safe routes for manned and unmanned systems in urban environments. The initial study found important individual differences related to perceived control and spatial abilities for finding safe routes and identifying targets in a simulated urban environment. Furthermore, the participants showed interesting effects related to agent reliability with information that the RoboLeader failed to provide (misses) more detrimental to finding a safe route than incorrect information (false alarms). This study is reported in an article submitted to the 6th ACM/IEEE International Conference on Human-Robot Interaction (*21*). Further experimentation, evaluating RoboLeader as decision support for robotic operators is planned for 2011 and 2012 as part of the SOURCE ATO. Finally, the RoboLeader simulation and results has been chosen as one of the demonstrations for the final project of the NATO's Human Factors and Medicine Panel Working Group on Supervisory Control (HFM-170). The demonstration will be documented in the HFM-170 final report for which a chapter has been submitted (*22*).

List of Symbols, Abbreviations, and Acronyms

ARL	U.S. Army Research Laboratory
ATO	Army Technology Objective
DRI	Director's Research Initiative
MIX	Mixed Initiative Experimental
NASA-TLX	National Aeronautics and Space Administration Task Load Index
OCU	Operator Control Unit
PAC	perceived attentional control
SA	situational awareness
SOURCE	Safe Operations for Unmanned Reconnaissance in Complex Environments
SpA	spatial ability
UAVs	unmanned aerial vehicles
UGVs	unmanned ground vehicles
UV	unmanned vehicles

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